International Academic Institute for Science and Technology

International Academic Journal of Science and Engineering
Vol. 8, No. 4, 2021, pp. 34-38.

ISSN 2454-3896

International Academic Journal of Science and Engineering

www.iaiest.com

Hybrid Data Decomposition-based Deep Learning for Bitcoin Prediction and Algorithm Trading

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Abstract

Since the beginning of time, money has played a crucial role in both storage and the exchange of goods and services. Fiat money, which is issued and managed by centralized banks and governments, is the modern form of money. Fiat money has several benefits, such as increased affordability, growth potential, economic stability, and global use, yet inflation results from printing more of it. Bitcoin operates on a highly secure distributed network's bottom root. Bitcoin is used for both transactions and asset storage because of its global acceptability. Bitcoin's primary benefits include being impenetrable and preventing double spending after a transaction is completed. The Bitcoin transaction is entirely transparent to all users on the network. As a result of its increased public appeal, Bitcoin continues to hold the top spot. The Deep Learning model of Multiplicative LSTM Networks is coupled with the Attention Mechanism for Bitcoin's next price prediction utilizing Technical Indicators in order to circumvent the gradient descent issue. Pattern-based indicators known as technical indicators are used to uncover hidden information in Bitcoin's historical raw data.

Keywords: Bitcoin, Convolutional Neural Networks, Singular Spectrum Analysis.

DOI:10.71086/IAJSE/V8I4/IAJSE0829
Received: 11 September 2021/Revised: 13 October 2021/Accepted: 10 November 2021/Published: 31 December 2021

Introduction

Money is a major factor in determining wealth and in transferring goods and services between individuals. Initially, people employed the barter system. Bartering is the exchange of products or services. One of the primary problems with the barter system was that there was no set way to determine how much amount was exchanged for each one (Chengzhao et al., 2019). This could lead to issues between the trading parties. Humans invented commodity money to solve this problem. Almost everyone in a community utilizes commodity money, which is nothing more than necessary products. They traded using tea, salt, tobacco, crops, and animals as currency. Additional risks to life are created when large quantities of the aforementioned products are stored and moved from one location to another. The introduction of paper money and non-precious coins issued by the government and regulated by the central bank concurrently transformed commodity money into representative money, ensuring that representative money could be exchanged for a predetermined amount of gold or silver (Baillon, 2019). In the 19th and early 20th centuries, the great majority of currencies were designed as representational money that served as the gold standard. Representative money has since been replaced by fiat money. The government now decides how much money is worth. Therefore, accepting any kind of payment other than "legal tender" money is now illegal (Passalis et al., 2021). Fiat money has several benefits, such as control, cost-effective printing, and ease of usage and carrying, but its limitless supply leads to inflation and economic bubbles. The limited supply of fiat money will be replaced with cryptocurrency, which is governed and safeguarded by a decentralized network known as the blockchain, in order to address the aforementioned problems (Kao et al., 2020). Virtual assets known as cryptocurrencies are used to purchase products, services, and other currencies. The mining procedure is how they are acquired. Blockchain technology limits the manufacturing of new units and verifies the transfer of credits by using strong cryptographic techniques to safeguard financial transactions. Distributed ledgers are used by blockchains to store these transactions. Each block contains a timestamp, transaction details, and a cryptographic hash of the previous block. Blockchains, which employ the Proof of Work consensus process and the SHA-256 cryptographic algorithm, are by design resistant to data tampering (Kao et al., 2020).

System Model and Assumptions

Cryptocurrencies are digital assets that are used to buy other currencies, goods, and services. Of all of them, Bitcoin is the most well-liked by the general population. Because of this, more and more people are interested in investing in Bitcoin in the hopes of earning profitable returns. As a result, academics, researchers, and investors are all very interested in forecasting the price of Bitcoin in the future. However, because Bitcoin is non-linear, it is still very difficult and unpredictable to anticipate its value with any degree of accuracy. Therefore, in order to develop trustworthy techniques for forecasting the value of Bitcoin, substantial research is required. Given the intricacy of Bitcoin's features and its price fluctuation over time, very few algorithms are able to forecast its price (Thakkar & Chaudhari, 2021). Multiplicative LSTM Network Architecture shown in Fig. 1.

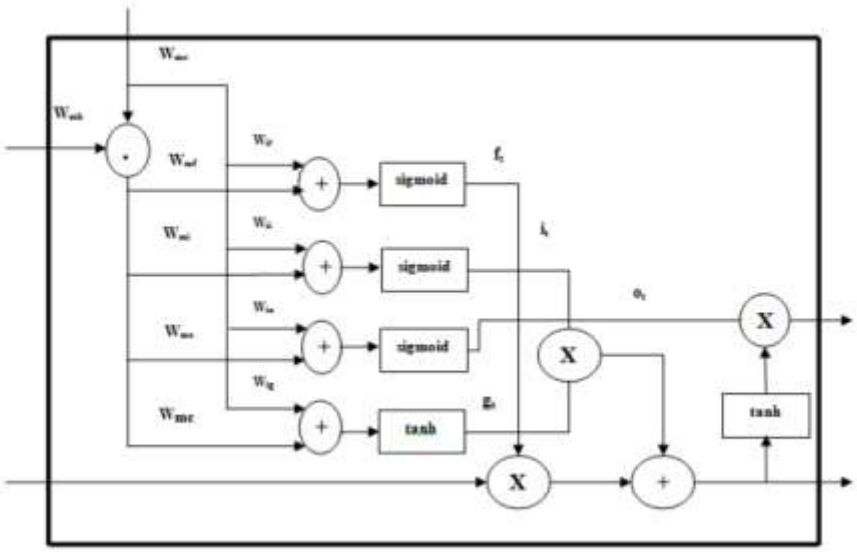
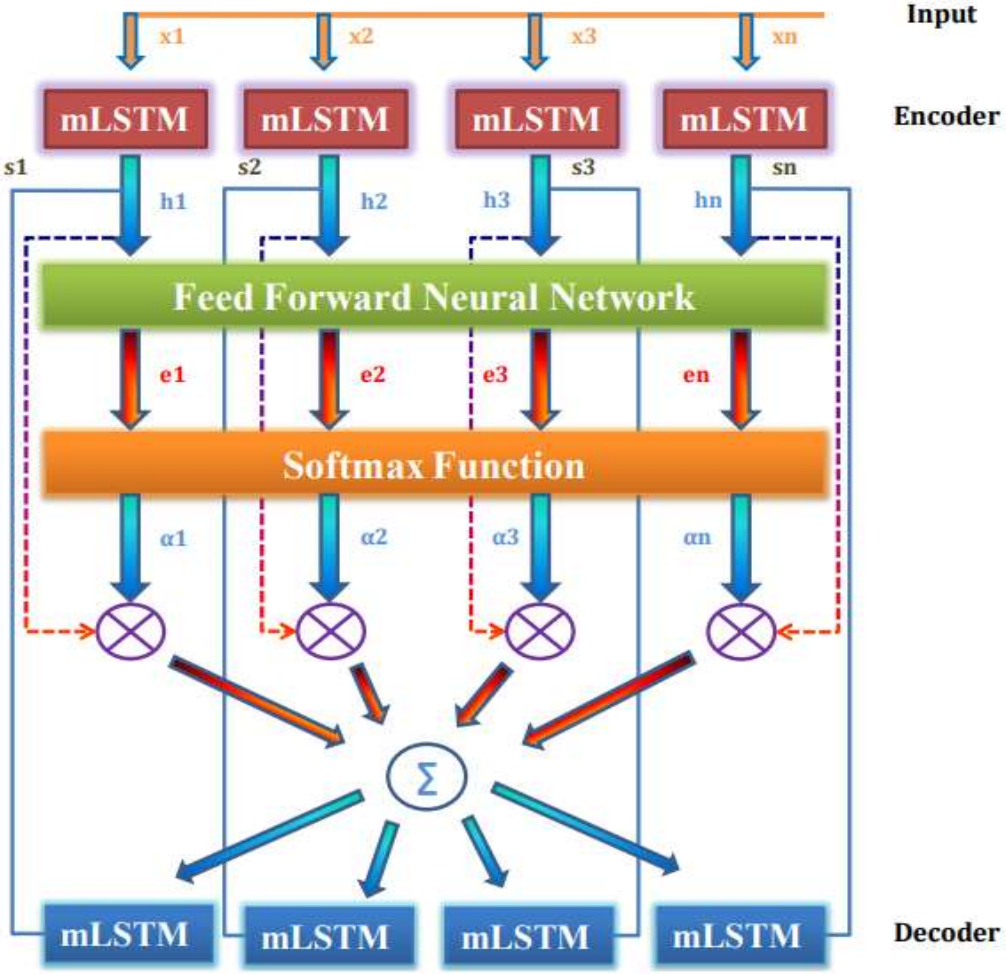


Fig. 1: Multiplicative LSTM Network Architecture

Therefore, it is now crucial to accurately calculate the value of Bitcoin in order to greatly support today's financial decisions. Since this problem falls under the time series prediction category, deep learning techniques and neural network models can be taken into consideration, particularly when considering price prediction of temporally oriented data (Feng et al., 2019). The Proposed VMD-LMH-Bi-LSTM shown in Fig. 2.



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Fig. 2: The Proposed VMD-LMH-Bi-LSTM

LSTM and RNN architectures are the most popular and successful Artificial Neural Network methods for identifying patterns in data sequences, including financial market data, numerical time series data, and data from governmental agencies. In contrast to other neural networks, RNNs and LSTMs have a temporal component and consider time and sequences. Conversely, recurrent networks employ both examples from their current input and data from prior periods as input (Chevallier et al., 2021).

Experiments

The initial dataset covers the period from April 29, 2013, to January 1, 2021, containing a total of 2805 data points. Fig. 3 provides a visual representation of the dataset. Two distinct groups of the dataset have been created: one for testing and one for training. The first 90% of the dataset is used to train the predictive model, while the remaining 10% is used to assess its performance. In particular, there are 2525 cases in the training dataset, which spans the period from April 29, 2013, to March 27, 2020. On the other hand, 280 occurrences from March 28, 2020, to January 1, 2021 are included in the testing dataset (Chevallier et al., 2021).

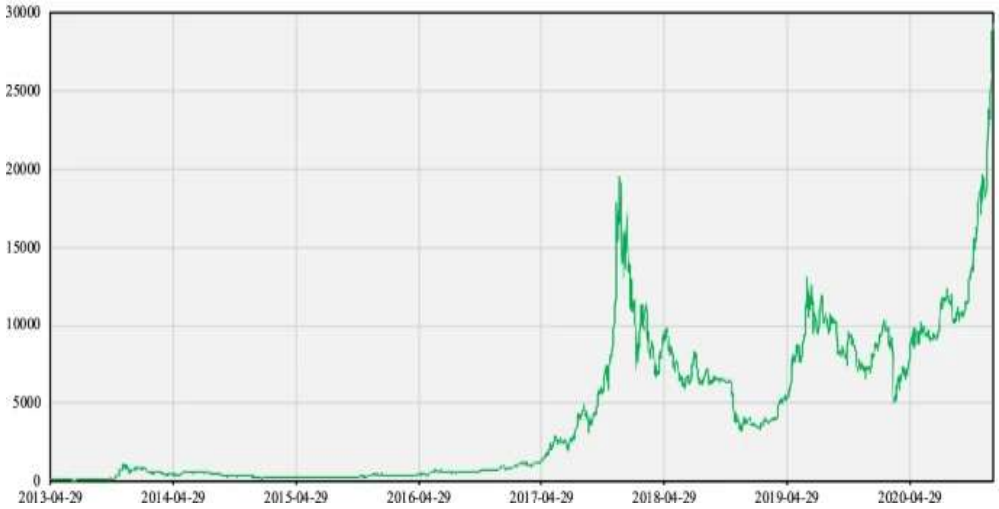


Fig. 3: A Visual Depiction of the Dataset

As seen in the following illustration, the data is adjusted and normalized using the 0-1 normalization approach in order to preserve uniformity in varying dimensions:

$$\widehat{x_t} = \frac{x_t - minx_t}{maxx_t - \min x_t} \qquad (3)$$

In this case, "xt" represents the exact value of the time series at a specified point in time, "t," and "maxxt" and "minxt" represent the highest and lowest recorded values in the time series, respectively. We have categorized each mode into three groups—low frequency, medium frequency, and high frequency—based on their recurrent patterns, using the patterns shown in Fig. 4 as our foundation. Regarding the market price of Bitcoin, M1 shows a cycle of almost three years, which is noticeably longer than the periods seen in other different modes. As a result, it is classified as low-frequency, reflecting the long-term and wide-ranging changes in Bitcoin market values between 2013 and 2019. Cycles spanning three to eight months are shown by modes M2 through M4, placing them in the medium-frequency category. These patterns can suggest price swings impacted by political and economic developments pertaining to Bitcoin and other cryptocurrencies.

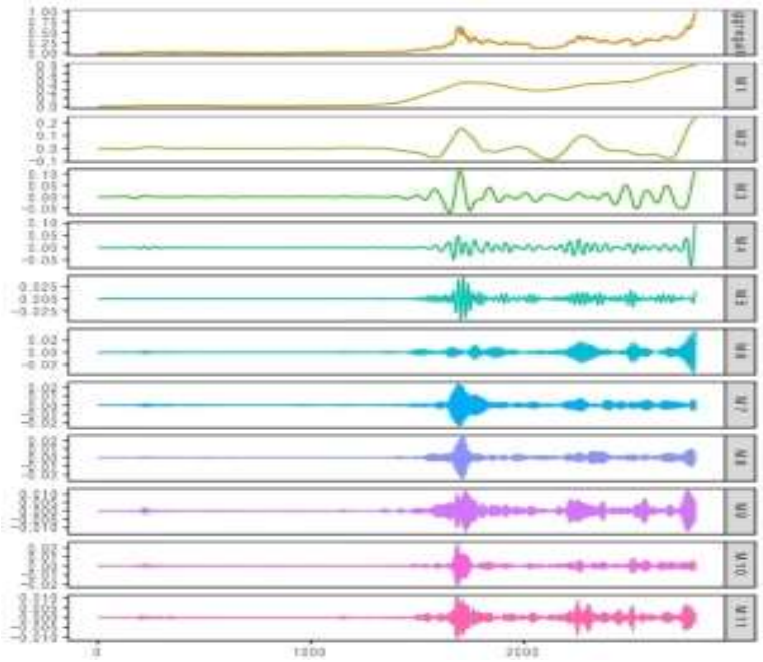


Fig. 4: VMD Decomposition Results for the Bitcoin Market Price

There are a number of benefits to the Multiplicative LSTM with Attention Mechanism model. First of all, it promotes effective data flow inside the network by facilitating improved information flow. Second, it facilitates parallelism in the training phase, making it possible to handle big datasets with ease. Finally, it produces better results because it is excellent at capturing long-term dependencies. Thus, the overall suggested model of mLSTM with Attention Mechanism yields favorable results whether the Technical Indicator is employed as well as when it is not.

Conclusion

Because Deep Learning's Artificial Neural Networks can handle large datasets with high dimensional data, it has been shown to be the most accurate model for predicting the price of bitcoin in the future. The best model with the memory capacity to store the long-term history was found to be LSTM Networks; nevertheless, this model has several limitations, such as vanishing gradients, a longer calculation time, and the inability to produce predictions with higher precision. In order to solve the problem of vanishing gradients and to increase computation accuracy and decrease computation time, a unique Deep Learning model of Multiplicative LSTM with Attention Mechanism was created in this study. More technical indicators were used to accomplish this in order to distinguish the present trend and movement from the previous values, which is more useful for forecasting future prices.

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